



Modelling current and future potential distributions of two desert jerboas under climate change in Iran

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ABSTRACT

Species distribution models (SDMs) are excellent tools to understand the factors that affect the potential distribution of several organisms at different scale. In this study, we analyzed the current potential distribution of the Blanford's Jerboa *Jaculus blanfordi* and the Arabian Jerboa *Jaculus loftusi* (Mammalia: Rodentia) in Iran and predicted the impact of climate change on their future potential distributions using two different modelling software packages: Maxent and sdm. Our results showed that precipitation was the most important variable affecting the potential distributions of *J. blanfordi* and *J. loftusi* in Iran. We also showed that the potential distributions of the two jerboas species are unlikely to be affected by climate change. All our models showed high levels of predictive performances. Thus, SDMs are a promising tool to complement data from laboratory and field studies to illuminate the biology and ecology of jerboa and inform management decisions.

1. Introduction

There is already undeniable evidence that animals and plants are being affected by climate change and global warming in their behavior and distribution. Several species are expected to increase/decrease and/or to shift their geographic distribution in response to climate change (Elith and Leathwick, 2009; Lawler, 2009). If greenhouse gas emissions will not be reduced, climate change could cause a quarter of animals and plants to become extinct. Thus, understanding how species distributions may be affected by direct/indirect impacts of climate change is a priority issue in ecology (Elith and Leathwick, 2009).

Climate change is expected to impact most organisms in ecosystems, including mammals (Morrison et al., 2018; Pacifici et al., 2018). Mammals play dominant roles in many systems (Jones and Safi, 2011). On one hand, regarding to the large mammals, they make up most of the terrestrial large-bodied predators in the world, and these apical animals have significant impacts on the ecosystems they inhabit (Jones and Safi, 2011). On the other hand, small mammals, including lagomorphs and rodents, are the primary prey for many mammalian, avian, and reptilian predators and they can affect the composition of vegetative communities through seed dispersion (Gill et al., 2009; Maron et al., 2012; Olofsson et al., 2014). Rodents typically comprise the largest and most diverse group of mammals in many ecosystems (Trani et al., 2007); thus, most of the changes in mammal abundances and

distributions resulting from climate change are expected to be in this group (Burns et al., 2003).

For most mammals, climate broadly defines their ecological niche. Therefore, future distributions are typically estimated by correlating climatic factors with the current ranges of the focal species and projecting these models forward in time (Levinsky et al., 2007). Abiotic variables, such as climate and/or elevation, have been successfully used to model the distribution of several large and small mammal species (Baltensperger and Huettmann, 2015; Bosso et al., 2018a; Kabir et al., 2017; Santos et al., 2017; Smeraldo et al., 2018). Species distribution models (SDMs) are excellent tools to understand the factors that affect the potential distribution of several organisms at different scale (Ellis, 2011; Pearson and Dawson, 2003). SDMs have been widely used to predict potential distribution of several organism in function of climate change (Bosso et al., 2017a; Cuenca-Lombrana et al., 2018; Kafash et al., 2018; Moritz et al., 2008; Nori et al., 2018; Slodowicz et al., 2018) and, regarding to rodents, several SDMs have proven to be effective to predict their current and future distribution (Farashi and Shariati Najafabadi, 2015; Gholamrezaei et al., 2016; Hamidi et al., 2018; Sadeghi and Malekian, 2017).

The Iranian three-toed jerboas (*Jaculus* spp., Erxleben, 1777, Dipodidae) inhabit different types of deserts and semi-arid environments. This genus is represented by three species [*Jaculus blanfordi* (Murray, 1884), *Jaculus loftusi* (Blanford, 1875) and *Jaculus thaleri*

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(Darvish and Hosseini, 2005)] presenting remarkable within-species variation, which has led to the recognition of several subspecies or species (Michaux and Shenbrot, 2017; Yusefi et al., 2019). The Blanford's Jerboa (*J. blanfordi*) occurs in southern and eastern desert plains of Iran, in southern and western parts of Afghanistan, as well as in some western part of Pakistan, Turkmenistan and Uzbekistan (Boratynski et al., 2012; Holden and Musser, 2005; Naderi et al., 2014; Shenbrot et al., 2016). The Arabian jerboa (*J. loftusi*) is distributed in most of the arid and sandy areas of North Africa, Arabian Peninsula, and south-western Iran (Amori et al., 2016; Michaux and Shenbrot, 2017; Yusefi et al., 2019). The Thaler's Jerboa (*J. thaleri*) has been observed only in some Iranian regions as the Kashmar (Khorasan-e Razavi province) and Bandan (South Khorasan province) areas near the Afghanistan (Darvish and Hosseini, 2005).

In Iran, jerboas species have been studied through conventional field and laboratory approaches so far (Dianat et al., 2013; Melnikova and Naderi, 2017; Mohammadi et al., 2016; Moshtaghi et al., 2016; Naderi et al., 2014; Shenbrot et al., 2016). However, no ecological research has investigated the current and future distribution of these small desert rodents. To understand the importance of the type of habitat on the distribution of these species, ecological studies are needed. Such studies can provide information for interpreting and predicting the trend of jerboas' potential distribution especially in desert regions in the face of ongoing climate change.

Desert-living species, especially those inhabiting flat desert areas as well as some jerboas species, are highly exposed to climate change as they are already living at their physiological limits (Vale and Brito, 2015). However, these small rodents are known to be nocturnal and tolerate high body and/or environmental temperatures; thus, they might be able to cope with the ongoing warming trend (Boyles et al., 2011; Levy et al., 2018). Accordingly, we hypothesize that climate change will not impact or lead to an increase of future potential distributions of *J. blanfordi* and *J. loftusi*. Here, we tested this hypothesis using two different modelling software packages: Maxent (Phillips et al., 2006) and sdm (Naimi and Araújo, 2016). We analyzed the current potential distribution of these two jerboas species in Iran and predicted the impact of climate change on their future potential distribution. We chose to exclude *J. thaleri* from our modelling study because the knowledge of this species is still scarce and unclear (Engelbrektsson, 2016). Furthermore, we focused our study only to Iran because this country is the main area of the distribution of *J. blanfordi* (Shenbrot and Molur, 2016) and is at the eastern-most edge of the *J. loftusi*'s range (Amori et al., 2016). Regarding this last point, at range margins of species distributions, regional/country models should be preferred over continental models with coarser resolution to identify suitable areas for peripheral populations (e.g. Astete et al., 2016; Vale et al., 2014).

2. Materials and methods

2.1. Study area and data collection

We considered the entire Iranian territory comprised between latitudes 39° – 26° and longitudes 43° – 63° (corresponding to ca. 1,648,000 km²).

We obtained presence records of *J. blanfordi* and *J. loftusi* from existing literature data (Karami et al., 2008; Khajeh et al., 2015; Ziaei, 2009), and from the public database Global Biodiversity Information Facility (<http://www.gbif.org>). We then critically reviewed this dataset by deleting unreliable, ambiguous or duplicate records and excluding those whose geographical location was not precisely defined. Care was taken to select presence records at a resolution matching as far as possible that available for the environmental digital representation. After this selection, we obtained 32 presence records of *J. blanfordi* and 19 occurrence data of *J. loftusi*. These presence records were used to generate current and future SDMs for the two jerboas species.

2.2. Eco-geographical variables

To carry out SDMs for *J. blanfordi* and *J. loftusi* in Iran, we considered initially the following set of eco-geographical variables: slope, aspect, soil type, elevation, water resources, land use, Normalized Difference Vegetation Index (NDVI), and 19 bioclimatic variables (Hijmans et al., 2005, Table S1). We used elevation with 30 m resolution (retrieved from <http://ncc.org.ir>) to generate slope and aspect. We downloaded the soil type and land use classification maps from the Forests, Range and Watershed Management Organization of Iran (<http://www.frw.org.ir/00/En/>). We obtained the 19 bioclimatic variables in 1 km spatial resolution from the WorldClim database (www.worldclim.org/current) (Hijmans et al., 2005, Table S1). Bioclimatic variables are biologically meaningful parameters derived from monthly temperature and rainfall values that describe annual trends, seasonality and extremes for species survival. These climate parameters have been typically used in ecological studies to evaluate the effect of climate on species distribution (Ashoori et al., 2018; Ashrafzadeh et al., 2018; Bosso et al., 2017b; Carli et al., 2018; Fois et al., 2018). We converted all the eco-geographical variables in ASCII files with a 30-arc sec resolution ($0.93 \times 0.93 \text{ km} = 0.86 \text{ km}^2$ at the equator). All analyses, conversions and calculations were made in ArcGIS 10.2.2. We identified the variables to be included in the current and future SDMs of *J. blanfordi* and *J. loftusi* using a correlation matrix by Pearson's technique between pairs of predictors. Specifically, we selected variables showing $r < 0.7$ to avoid correlated eco-geographical variables (e.g. Bosso et al., 2018b; Kabir et al., 2017; Morán-Ordóñez et al., 2018; Niittynen and Luoto, 2018). Finally, from this set of predictors, we considered only those most relevant to the species' ecological requirements and this led to a final set of EGVs (Table S2) used to model current distribution of two jerboas species in Iran.

2.3. Selection of climate models to estimate future distributions

We modelled future SDMs for *J. blanfordi* and *J. loftusi* in Iran using one global climate models. We used two representative concentration pathways (RCPs) (RCP 2.6 and RCP 8.5) for only one time step: 2050 (average for 2041–2060) (Ebrahimi et al., 2017; Meinshausen et al., 2011; Riahi et al., 2011). We used the CCSM4 climate model (Gent et al., 2011). This model is one of the most efficient global climate projection to predict the influence of future climatic changes on the distribution of animal and plant species (e.g. Farashi and Erfani, 2018; Liang et al., 2018; Salas et al., 2018). It has already been successfully tested in similar habitats (Abdelaal et al., 2019; Al-Qaddi et al., 2017; Gonçalves et al., 2018). RCPs are greenhouse gas concentration trajectories adopted by the IPCC for its fifth Assessment Report in 2014 (<https://www.ipcc.ch/report/ar5/wg2/>). According to Meinshausen et al. (2011), the first scenario (RCP 2.6) represents an optimistic projection characterized by a very low concentration and emissions levels of greenhouse gases. The second scenario (RCP 8.5) represents a pessimistic projection with high levels of concentrations and emissions of greenhouse gases.

2.4. Modelling procedures and validations

We built SDMs using two different modelling software packages: 1) Maxent version 3.4.1 k (Phillips et al., 2006) and 2) sdm (Naimi and Araújo, 2016) in the R platform version 3.5.3 (R Development Core Team, 2017). Maxent is a machine learning algorithm that allows SDMs to be generated using presence-only data, making it an effective tool with which to predict species distribution when obtaining presence-absence data is logistically impractical (Phillips et al., 2006). Maxent has become the most popular for both its ease of use and functionality (Morales et al., 2017). sdm is an object-oriented reproducible and extensible framework for species distribution modelling in R that unified different implementations of SDMs in a single framework. It provides an

easy-to-use comprehensive framework to perform the entire modelling process within the same environment using different state-of-the-art approaches (Naimi and Araújo, 2016). From sdm package, we considered eight modelling techniques (e.g. Ducci et al., 2015; Smeraldo et al., 2018), as follows: generalized linear model (GLM), generalized additive model (GAM), random forest (RF), support vector machine (SVM), multivariate adaptive regression splines (MARS), boosted regression tree (BRT), flexible discriminant analysis (FDA), Classification and regression trees (CART). The combined model unifies the strengths of several SDM approaches while minimizing the weakness of any particular model (Salas et al., 2018).

We tested the predictive performance of the models with different methods: the receiver operated characteristics, analyzing the area under curve (AUC) (Fielding and Bell, 1997); and the true skill statistic (TSS) (Allouche et al., 2006). AUC assesses the discrimination ability of the models and its value ranges from 0 (equalling random distribution) to 1 (perfect prediction). AUC values > 0.75 correspond to high discrimination performances (Fielding and Bell, 1997). TSS compares the number of correct forecasts, minus those attributable to random guessing, to that of a hypothetical set of perfect forecasts. It considers both omission and commission errors, and success as a result of random guessing; its values range from -1 to +1, where +1 corresponds to perfect agreement and zero or less to a performance that is no better than random (Allouche et al., 2006).

2.5. Comparing current and future models of *J. blanfordi* and *J. loftusi*

We transformed the final maps of both modelling approaches into presence-absence maps using the threshold that maximized sensitivity (the percentage of correctly predicted presence) and specificity (the percentage of correctly predicted absence; Fielding and Bell, 1997). Such parameter has been widely used (e.g. Raath et al., 2018; Smeraldo et al., 2018); and constitutes one of the most accurate threshold (Liu et al., 2005). We then quantified the changes in the predicted surfaces, comparing all the current and future presence/absence maps of *J. blanfordi* and *J. loftusi* in Iran. All the presence/absence maps indexed the environmental suitability of two jerboas species with values of 0 (unsuitable) and 1 (suitable). We computed the changes in the predicted ecological extent of *J. blanfordi* and *J. loftusi* in Iran, as follows: we converted the presence/absence maps to raster layers with float data-type using ArcGIS 10.2.2, then we calculated the number of cells (pixels) among projected climatic extent using zonal statistics in spatial analyst tools in ArcGIS 10.2.2. Finally, we converted the differences in the mean number of cells of potential habitats to surface area (km²) (e.g. Abdelaal et al., 2019).

3. Results

3.1. Current SDMs of *J. blanfordi* and *J. loftusi*

Both modelling software packages showed two separate suitable areas for each of the two studied species in Iran (Fig. 1a and d). *J. blanfordi* occurred in the central and east areas of the Iran. It was enclosed, from north to south, between the provinces of Qazvin and Sistan and Baluchestan (Fig. 1a and d), while, from west to east, it was placed between the provinces of Khuzestan and south Khorasan (Fig. 1a and d). *J. loftusi* was found in the western small areas of Iran situated, from north to south, between the provinces of Kermanshah and Sistan and Baluchestan (Fig. 2a and d), while, from west to east, it was placed between the provinces of Khuzestan and Sistan and Baluchestan (Fig. 2a and d).

The analysis of single variable contributions showed that precipitations (30.7%) and slope (12.4%) were the main factors influencing performance of *J. blanfordi*' models (Table S3). We found that elevation (65.1%) and precipitation (14.4%) were the main variables influencing model performance of *J. loftusi*' outputs (Table S3). Based

on the model's predictions, *J. blanfordi* occurred in area with low precipitation and slope values (Fig. S2), while *J. loftusi* preferred areas with low precipitation and elevation values (Fig. S3).

All our models showed high levels of predictive performances as can be seen from the values of AUC (> 0.7) (Figs. S1a and S1b) and TSS (> 0.7) (Figs. S1c and S1d).

3.2. Future SDMs of *J. blanfordi* and *J. loftusi*

The future models also essentially predicted two distinct suitable areas for *J. blanfordi* and *J. loftusi* in Iran (Fig. 1b, c, e and f). We found a new large suitable areas placed in the Khorasan province for *J. blanfordi* using sdm package with RCPs 2.6 and RCPs 8.5 at 2050 (Fig. 1e and f). We detected no difference in suitable areas for *J. blanfordi* using the Maxent package (Fig. 1b and c). Regarding to *J. loftusi*, we identified a core areas of habitat suitability placed in the province of Khuzestan (Fig. 2b, c, e and f). Moreover, analyzing Maxent models, we also found a new small suitable areas in the province of Kerman with RCPs 2.6 at 2050 (Fig. 2b).

The analysis of single variable contributions showed that precipitations (49.4%), slope (22.3%) and temperature (14.87%) were the main factors influencing performance of *J. blanfordi*' models with RCP 2.6 at 2050 (Table S3). Precipitation (58.2%) and slope (20.6%) were again the most influential variables for *J. blanfordi* with RCP 8.5 at 2050 (Table S3). We found that elevation (84.9%) and precipitation (10.2%) were the main variables influencing model performance of *J. loftusi*' models with RCP 2.6 at 2050 (Table S3). Elevation (66.6%) and precipitation (23.7%) were also the variables with the highest percentage of contribution for *J. loftusi* with RCP 8.5 at 2050 (Table S3). Based on the model's projections, regardless of RCPs used in this study, *J. blanfordi* occurred in area with low precipitation and slope values (Figs. S4 and S5), while *J. loftusi* preferred areas with low precipitation and elevation values (Figs. S6 and S7).

3.3. Comparing current and future models

Current suitable habitat for *J. blanfordi* amounted to ca. 386,000 km² and 206,000 km², using Maxent and sdm, respectively (Table 1). *J. loftusi*'s current suitable habitat corresponded to ca. 70,500 km² using Maxent and 37,000 km² with sdm (Table 1). Through the Maxent software, we detected a suitable surface > 470,000 km² for *J. blanfordi* independently of the RCPs at 2050 and a suitable areas for *J. loftusi* of ca. 85,000 km² and ca. 103,000 km² for a RCP 2.6 and RCP 8.5, respectively (Table 1).

4. Discussion

4.1. Model performances and validations

According to available data from laboratory and field studies, both Maxent and sdm provided accurate predictions of current potential distributions of *J. blanfordi* and *J. loftusi* in Iran. However, we noted that the maps of habitat suitability were more conservative using the sdm rather than Maxent. We hypothesize that the different software outputs were due to the interaction among the presence records, the eco-geographical variables and the type of algorithms included in the two modelling software packages. Our findings highlight the importance of multi-methods approaches in predicting species distribution (Hao et al., 2019). Consequently, if conservation issues should be addressed, this influence makes particularly important the adoption of consensus methods for deriving one univocal prediction from an ensemble of different models (e.g. Marmion et al., 2008).

Our SDMs showed considerable performance in estimating distribution of *J. blanfordi* and *J. loftusi* in Iran, as supported also by validation results. AUC values such as the ones that we obtained (> 0.7) are among the highest reported for published models (e.g. Kabir et al.,

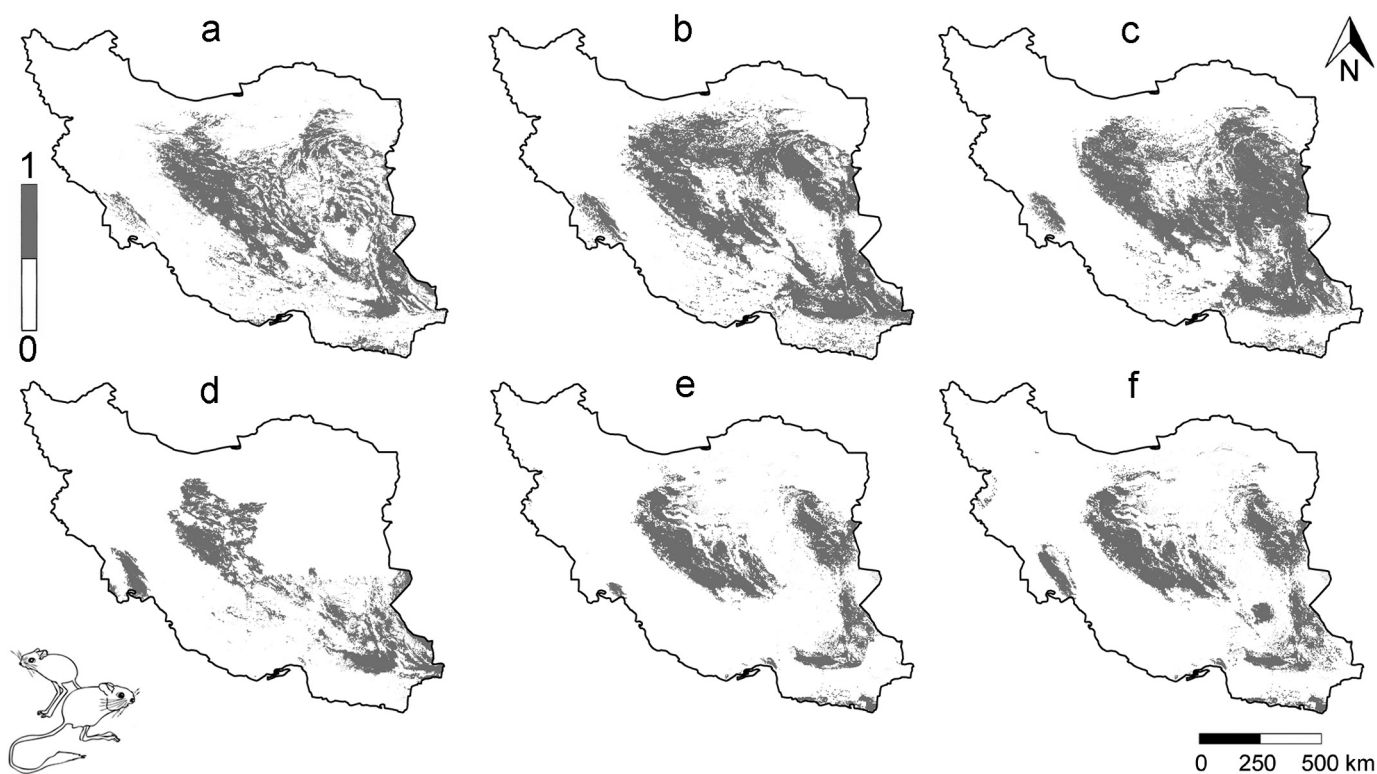


Fig. 1. SDM outputs for *J. blanfordi* in Iran for the current and CCSM4 models obtained using Maxent and sdm for two representative concentration pathways (RCPs) (RCP 2.6 and RCP 8.5) and one time period 2050. Presence-absence maps show the probability of presence: 0 (white) and 1 (grey). The outputs as follows: a = Current Maxent; b = CCSM4 Maxent RCP 2.62050; c = CCSM4 Maxent RCP 8.52050; d = Current sdm; e = CCSM4 sdm RCP 2.62050; f = CCSM4 sdm RCP 8.52050.

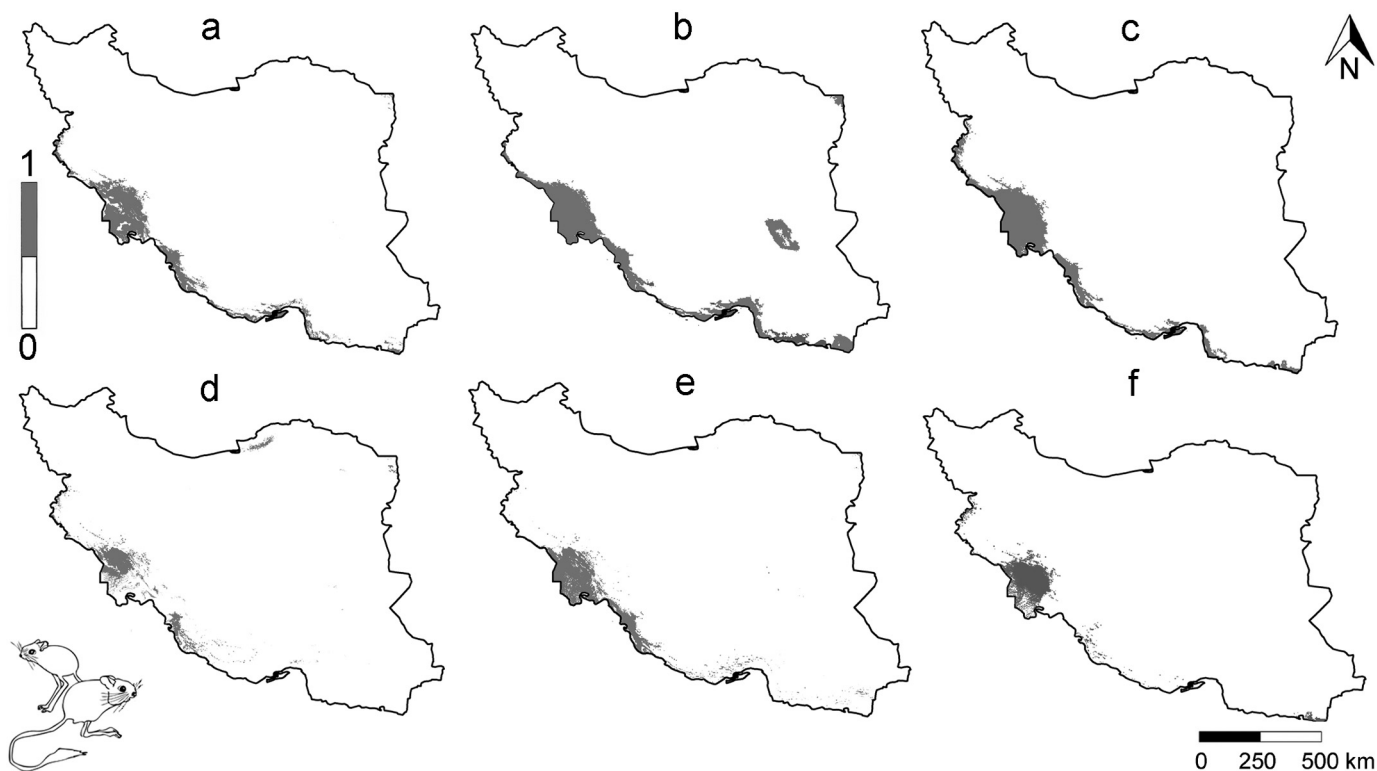


Fig. 2. SDM outputs for *J. loftusi* in Iran for the current and CCSM4 models obtained using Maxent and sdm for two representative concentration pathways (RCPs) (RCP 2.6 and RCP 8.5) and one time period 2050. Presence-absence maps show the probability of presence: 0 (white) and 1 (grey). The outputs as follows: a = Current Maxent; b = CCSM4 Maxent RCP 2.62050; c = CCSM4 Maxent RCP 8.52050; d = Current sdm; e = CCSM4 sdm RCP 2.62050; f = CCSM4 sdm RCP 8.52050.

Table 1

Amount of km² and percentage of suitable areas for *J. blanfordi* and *J. loftusi* in Iran obtained using Maxent and sdm for the current and CCSM4 models for two representative concentration pathways (RCPs) (RCP 2.6 and RCP 8.5) and one time period 2050.

Modelling package	Model	<i>J. blanfordi</i>		<i>J. loftusi</i>	
		km ²	%	km ²	%
Maxent	Current	385,960	23	70,545	4
	CCSM4 2050 RCP 2.6	472,150	29	103,559	6
	CCSM4 2050 RCP 8.5	490,723	30	85,754	5
sdm	Current	205,942	13	37,164	2
	CCSM4 2050 RCP 2.6	254,213	15	51,664	3
	CCSM4 2050 RCP 8.5	273,225	17	37,667	2

2017; Moradi et al., 2019; Morán-Ordóñez et al., 2018; Russo et al., 2015; Smeraldo et al., 2018) and demonstrate a high predictive capacity of habitat suitability (Elith et al., 2010; Swets, 1988). Our study was further supported by the TSS values (Gillard et al., 2017; Russo et al., 2015; Smeraldo et al., 2018). We noted that both model evaluation results, AUC and TSS, were strongly different depending upon the modelling software package applied. These differences in model evaluation results due to use of different software packages are already known in literature (e.g. Shabani et al., 2016). Our results showed that Maxent obtained the higher AUC values than sdm for both the jerboas species and for all the climate models. Likewise, Maxent had the best performances respect to ensemble models in the study carried out by Bombi et al. (2009) on the Bedriaga's rock lizard distribution in Sardinia. This our result is partially in agreement with previous comparative analyses of different modelling approaches (e.g. Elith et al., 2006; Shabani et al., 2016), which highlighted Maxent as one of the top-performing algorithms (e.g. Bombi et al., 2009). Our results showed also that GAM, GLM and RF obtained the best TSS values for *J. blanfordi*, while *J. loftusi* obtained a very high values of TSS essentially using the RF modelling techniques. Furthermore, our study confirms that each one of these model software packages (Maxent and sdm) provides slightly different results on projections and that it may be safer to use always different validation methods. In fact, it is very important to remember that modelling study should be currently validated at least by two model validation methods. In this way, the model performance should be assessed more reliable than when we use only one validation method (Shabani et al., 2016).

4.2. Model limitations

The main limitation of our study was that we used only one climate model in future projection of *J. blanfordi* and *J. loftusi* in Iran for 2050. Usually, modelling study should use different climate models to validate the results obtained with future projection (e.g. Bosso et al., 2017a; Mariotti et al., 2015; Trnka et al., 2014). Having said that, for our work we used CCSM4 climate model that is currently one of the most efficient global climate projection to predict how future climatic change can affect the distribution of animal and plant species (e.g. Farashi and Erfani, 2018; Liang et al., 2018; Salas et al., 2018). Furthermore, CCSM4 climate model has already been successfully tested in desert habitats similar to those in Iran (Abdelaal et al., 2019; Al-Qaddi et al., 2017; Gonçalves et al., 2018). This study, therefore, should be used as the starting point for carrying out further modelling studies to analyze the impact of climate changes on desert jerboa species in Iran, as in so many other parts of the world.

Each of the modelling software packages used in this study (Maxent and sdm) has methodological, spatial and temporal limitations that constrain their predictive power especially in future projection (e.g. McMahon et al., 2011). SDMs usually consider the species as static and independent entities, although their dynamics and their role in

ecological networks are both known to be essential. However a new generation of models is emerging that focuses on more robust biological hypotheses and meets some of the challenges posed by each limitation (e.g., Gallien et al., 2010; Thuiller et al., 2008).

4.3. Ecological considerations

SDMs are a modern approach to assess the potential effect of climate change on biodiversity. This modelling tool has widely been used to estimate the effect that climate change can have on already sensitive ecosystems, such as desert areas. Similarly to Vale and Brito (2015), our results showed that precipitation was the most important eco-geographical variable to explain current and future potential distributions of *J. blanfordi* and *J. loftusi* in Iran. In arid regions, changes in precipitation might even more dramatically impact biodiversity in comparison to other ecosystems (Kotler and Brown, 1988; Vale and Brito, 2015). Indeed, desertification has been associated to populations decreases, extinctions and range shifts in species adapted to aridity as in the Sahara-Sahel (e.g. Brito et al., 2014). Current and future distributions of the Iranian jerboas did not show a change in suitable surfaces, confirming our starting hypothesis that these species would not be affected by climate change. This congruence between current and future potential distributions could be explained by two reasons: 1) these two species are already well adapted to live in arid environmental conditions; and 2) the current environmental conditions in Iran will not differ much from those expected in 2050.

In summary, our results indicate that the Iranian jerboas, despite being desert species already living at their physiological limits (Kefi et al., 2007; Vale and Brito, 2015), might not be negatively impacted by climate change, as shown for other species (Parmesan, 2006). However, this might not be always the case. In fact, some organisms might be able to adapt to changing local conditions also through phenotypic plasticity (Raffini and Meyer, 2019), but many species are more likely to shift their distribution or even become extinct in response to the rise of global temperatures and change in precipitation (Dyderski et al., 2018; Williams and Blois, 2018). Therefore, we need accurate predictions of the effects that climate change might have on biodiversity to design the most proactive conservation strategies (Yalcin and Leroux, 2017). To this end, SDMs can be an extremely useful instrument, especially when only limited knowledge is available. We conclude that despite some limitations of modelling approaches, SDMs should be considered as a valuable tool to complement laboratory and field data in order to obtain a better understanding of the biology and ecology of the jerboa species.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.ecoinf.2019.04.003>.

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